Simulating Makeup through Physics-based Manipulation of Intrinsic Image Layers

Chen Li[1*] Kun Zhou[1] Stephen Lin[2]
[1]State Key Lab of CAD&CG, Zhejiang University [2]Microsoft Research

Abstract

We present a method for simulating makeup in a face image. To generate realistic results without detailed geometric and reflectance measurements of the user, we propose to separate the image into intrinsic image layers and alter them according to proposed adaptations of physically-based reflectance models. Through this layer manipulation, the measured properties of cosmetic products are applied while preserving the appearance characteristics and lighting conditions of the target face. This approach is demonstrated on various forms of cosmetics including foundation, blush, lipstick, and eye shadow. Experimental results exhibit a close approximation to ground truth images, without artifacts such as transferred personal features and lighting effects that degrade the results of image-based makeup transfer methods.

1. Introduction

A common way to alter or improve one's facial appearance is through the application of makeup. Not only can it be used for beautification purposes, but studies have shown that appropriate use of makeup can make a woman appear more competent and trustworthy than without it [13]. The key to a flawless finish that looks light and natural is to use cosmetic products well-suited for the particular face, as well as to master the application skills. Determining the suitability of a particular makeup product requires a person to try it and view the result. While this may be easy to do at a cosmetics counter, it cannot conveniently be done, for example, at home when making an online purchase.

To address this problem, several techniques have been proposed for simulating the appearance of makeup in an image of the user. These techniques can generally be categorized into two approaches. The first approach is to synthesize makeup effects through computer graphics rendering [6, 3, 12, 14]. These methods use geometric models of faces and reflectance models of skin and makeup to compute a realistic result. While impressive renderings have been produced in this manner, they may be slow to compute and require detailed data such as the user's face geometry and skin reflectance, which are impractical to obtain in many settings. The other approach is image based, where the appearance of makeup on one person's face in a reference image is transferred to the user's face in a target image [5, 16]. These methods are much more convenient to apply than rendering-based techniques. However, they require restrictive assumptions such as similar lighting conditions in both the reference and target images. In addition to transferring makeup, these techniques may also transfer personal features such as wrinkles and blemishes from the reference to the target. Furthermore, they do not realistically model the shading effects of cosmetics, such as the reduction of subsurface light scattering in the skin when it is covered with foundation.

In this work, we present a technique that overcomes these limitations of prior image-based methods without requiring the heavier computation and detailed user data needed by rendering-based approaches. Our method accomplishes this through decomposing the target image into reflectance layers that can be efficiently transformed into their makeup equivalents using proposed adaptations of physically-based reflectance models. The decomposition makes use of recent advances in intrinsic image estimation [9, 20] to separate the target image into albedo, diffuse shading, and specular highlight layers. For each of these layers, we present transformations which alter them in a way that preserves the identity of the user while conveying the appearance of makeup based on its optical properties. The layers are then combined to form the final makeup result, without requiring more than an ordinary image from the user.

Since this method applies makeup properties to a target image instead of transferring appearance data from a reference image, constraints on lighting and artifacts due to transmitted personal features are both avoided. Through the use of physically-based reflectance models, the shading effects of cosmetics are more realistically simulated as well.

*This work was done while Chen Li was an intern at Microsoft Research.

We have applied our approach on various makeup products that include foundation, blush, lipstick, and eye shadow. Results are efficiently generated in about 1.5 seconds for a 600×400 photograph[1], and they visually compare well to ground truth images.

2. Related Work

In this section, we review recent methods related to digital makeup, including works on makeup transfer [5, 16], makeup suggestion [14, 10], and physically-based cosmetics rendering [6, 3, 12].

Makeup transfer generates makeup in a target face image using reference images as an example. In [16], the example consists of two images of the same face, before and after makeup is applied. To add makeup to a new face image, the ratio of color values between corresponding pixels in the "after" and "before" examples is used to modify the target image, and then a gradient editing process is applied to make the target image gradients more similar to the gradients in the makeup example. In [5], only an "after" image is used as a reference, since "before" images are more difficult to obtain. This method decomposes both the reference and target image into three layers: face structure, skin detail, and color. Then the makeup effect is transferred layer by layer, with alpha blending for color, a linear combination for skin detail, and gradient editing for face structure. Since image gradients are affected by illumination, the gradient editing in both of these methods will transfer lighting effects from the reference to the target image. The two methods also may transfer personal facial features, since any visible blemishes, bumps and wrinkles will be included with the reference skin detail in [5], and smooth skin in the reference image may replace personal details in the target image in [16] because of its gradient editing. Our method avoids these problems by adjusting facial appearance in the target image using adaptations of physically-based reflectance models, instead of transferring image appearance. The use of these models also leads to more realistic shading effects that cannot be captured in these makeup transfer techniques.

Makeup suggestion aims to find the best makeup for a given face. In [14], a database of 56 female faces is captured both without makeup and with professionally applied makeup. A mapping from the space of facial appearances to that of makeup is then learned from the database, and makeup is suggested for a target face based on this mapping. The makeup is synthesized through adjustments of various appearance properties including specularity, glossiness, and scattering strength. Applying these adjustments to a target face involves 3D face reconstruction and lighting measurement to recover its appearance properties, making this approach less practical for general settings. By contrast, our method applies changes to reflectance layers that can be decomposed from an ordinary image. Another technique for makeup suggestion learns the relationships among high-level beauty-related attributes, mid-level beauty attributes, and low-level image features [10]. Makeup is synthesized simply through alpha blending, without consideration of diffuse or specular reflectance properties.

[1] Our algorithm was implemented on a 2.93 Ghz PC with 8 GB of RAM.

	Albedo	Diffuse shading	Specular highlights
Foundation, lipstick	✓	✓	✓
Eye shadow, blush	✓		

Table 1. Intrinsic image layers affected by different cosmetics.

Physically-based cosmetics rendering addresses the digital makeup problem from the computer graphics perspective. Realistic makeup appearance is synthesized using rendering systems that incorporate physical models on the interaction of light with cosmetics and facial skin. For accurate modeling of cosmetic foundation, its optical properties have been carefully analyzed and measured [3, 12]. The state-of-the-art method for rendering 3D makeup effects [6] combines the Kubelka-Munk model for radiance transfer in material layers [8] and a screen-space skin rendering approach for simulating the subsurface scattering effects inside human skin [7]. To utilize such rendering techniques, the 3D facial geometry and skin reflectance properties of the target face need to be acquired. Our method also employs these reflectance models but instead uses them to adjust the reflectance layers of a target image.

3. Models of Intrinsic Layer Change

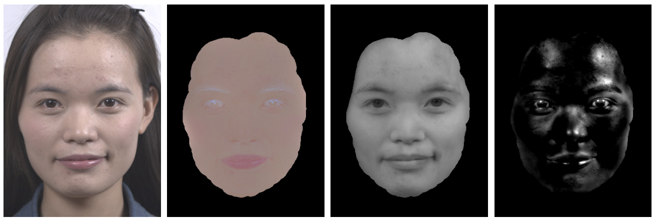
In our digital makeup approach, we model how cosmetics change each of the three intrinsic image layers according to physically-based models of reflection. With these intrinsic layer change models, we can simulate the appearance of various cosmetics according to their physical properties such as coating thickness, surface roughness, and scattering and absorption coefficients.

In this work, we consider four types of makeup, namely foundation, lipstick, eye shadow and blush. Other kinds of cosmetics can be modeled in a similar manner. The intrinsic image layers that are affected by each of the four cosmetic types is shown in Table 1. In the following, we describe the intrinsic image decomposition and present the models of layer change.

3.1. Image decomposition

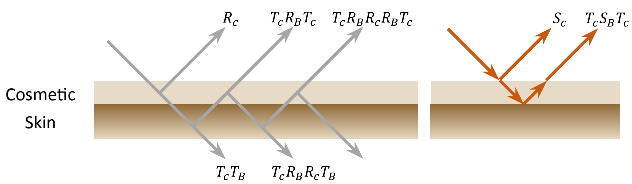
An image I can be expressed in terms of three intrinsic image components, namely albedo A, diffuse shading D and specular highlights S:

$$I = A \cdot D + S. \tag{1}$$



(a) (b) (c) (d)

Figure 1. A decomposition example. (a) Input image. (b) Albedo layer. (c) Diffuse shading layer. (d) Specular highlights layer. The layers for diffuse shading and specular highlights have been scaled for better visualization.



(a) (b)

Figure 2. Light paths through cosmetic and skin layers. (a) For computing albedo. (b) For computing specular highlights.

We decompose an image into these three intrinsic image layers by first extracting the specular highlight component using the color-space based method described in [9]. The remaining albedo and diffuse shading components are then separated using the Retinex-based intrinsic image solver in [20]. We note that though the work in [9] is designed to separate a face image into the three layers by itself, its separation of albedo and diffuse shading relies on priors for skin color, which makes it unsuitable for decomposition of faces with makeup. An example of this decomposition is displayed in Figure 1.

In modeling the effects of cosmetics on the three layers, we consider the corresponding layers of a barefaced image I_B without makeup, and a face image I_M with makeup. Their respective decompositions can be expressed as

$$I_B = A_B \cdot D_B + S_B, \tag{2}$$

$$I_M = A_M \cdot D_M + S_M. \tag{3}$$

Since there exists scale ambiguity in the decomposition of A and D, we normalize the diffuse shading layer so that its maximum is equal to one, and rescale the albedo layer accordingly.

3.2. Layer change

The application of makeup causes changes in the appearance of the intrinsic layers. In the following, we formulate these changes based on physically-based reflectance models for albedo and specular highlights, and on an approximate model for diffuse shading.

3.2.1 Albedo change

The Kubelka-Munk model [8] was originally proposed for representing how the color of a substrate changes after being coated by paint of a given composition and thickness. Since then, it has been used for modeling color for various layered surfaces including makeup on skin [6]. For a coating of cosmetics, the Kubelka-Munk model expresses its reflected color R and transmitted color T as

$$R = \frac{\sinh bSt}{a \sinh bSt + b \cosh bSt}, \tag{4}$$

$$T = \frac{b}{a \sinh bSt + b \cosh bSt}, \tag{5}$$

where S and K are wavelength-dependent scattering and absorption coefficients per unit length, $a = 1 + \frac{K}{S}$, $b = \sqrt{a^2 - 1}$, and t is the thickness of cosmetic coating. In this work, we model wavelength-dependence at the level of RGB channels.

To determine how the albedo A_B of barefaced skin is changed by makeup into the resulting albedo A_M, we consider the paths of light reflection among the cosmetic and skin layers, as shown in Figure 2(a). As light scatters within the cosmetic layer c, it is transformed by color R_c, and as it passes through layer c, it is transformed by color T_c. The final color from the sum of these light paths can be formulated as a sum of a geometric series [6]:

$$\begin{aligned} A_M &= R_c + T_cR_BT_c + T_cR_BR_cR_BT_c + \cdots && (6) \\ &= R_c + \frac{T_c^2 R_B}{1 - R_cR_B}, && (7) \end{aligned}$$

where $R_B = A_B$. With this formula, the albedo of a bare face can be changed to the albedo that is seen with makeup, based on the cosmetic's wavelength-dependent scattering and absorption coefficients and thickness.

3.2.2 Diffuse shading change

In some previous work [5], it is assumed that foundation hides small-scale skin features such as wrinkles and bumps. However, this is not true in practice[2]. Bare skin is translucent with considerable subsurface scattering of light. This subsurface scattering creates a blurring effect [7] that reduces shading variations caused by small-scale surface features like wrinkles. By contrast, cosmetics like foundation are relatively opaque and reduce translucency. A makeup layer thus reduces subsurface scattering and actually makes wrinkles more apparent as illustrated later in Fig. 7.

To model the change in diffuse shading caused by cosmetics, we make use of the subsurface scattering approximation proposed in [7], which models subsurface scattering

[2] http://beauty.about.com/od/spassalons/a/How-To-Conceal-Wrinkles-On-Your-Face.htm

as a Gaussian convolution of opaque diffuse shading. As makeup is more opaque than skin, we model the relationship between diffuse shading with and without makeup as

$$D_M * G(\sigma) = D_B, \tag{8}$$

where σ is a Gaussian blur kernel defined as

$$\sigma_x = \frac{\alpha \cdot t}{d + \beta \cdot |\nabla_x d|}, \tag{9}$$

$$\sigma_y = \frac{\alpha \cdot t}{d + \beta \cdot |\nabla_y d|}, \tag{10}$$

with α denoting the global subsurface scattering level, β modulating how the subsurface scattering varies with depth gradient, t being the thickness of the makeup, and operators ∇_x and ∇_y computing the gradient of the depth field d along the x and y directions. Since our input is images without depth data, we obtain a rough approximation of the depth field d using the single-image 3D face reconstruction algorithm in [19].

To solve for D_M in Eq. (8), we compute the deconvolution by optimizing the following energy function:

$$\underset{D_M}{\operatorname{argmin}} \|GD_M - D_B\|^2 + \lambda \|\Delta D_M\|^2, \tag{11}$$

where D_M and D_B are represented in vector format, each row of matrix G contains the convolution coefficients of $G(\sigma)$, Δ is the Laplacian operator, and λ balances the deconvolution and smoothness terms. We set $\lambda = 0.1$ in our work. This optimization can be done by solving the following over-constrained sparse linear equations:

$$\begin{bmatrix} G \\ \sqrt{\lambda}\Delta \end{bmatrix} \begin{bmatrix} D_M \end{bmatrix} = \begin{bmatrix} D_B \\ 0 \end{bmatrix}. \tag{12}$$

We use the sparse QR factorization solver [2] in *SuiteSparse*[3] to solve this sparse linear system.

3.2.3 Specular highlights change

An important visual effect of cosmetics is in changing the appearance of specular highlights. For example, foundation generally reduces highlights to give a smoother appearance, and lipstick tends to increase highlights to accentuate the features of the lips. As the Kubelka-Munk model does not deal with specular reflections, we turn to the Torrance-Sparrow model [17], a physically-based microfacet model for surface reflectance:

$$f_s = \frac{1}{\pi} \frac{UP}{(N \cdot \omega_i)(N \cdot \omega_o)} F_r(\omega_i \cdot H, \eta) \tag{13}$$

[3]SuiteSparse: a Suite of Sparse matrix packages, at http://www.cise.ufl.edu/research/sparse/SuiteSparse/

where

$$U = \min\{1, \frac{2(N \cdot H)(N \cdot \omega_o)}{(\omega_o \cdot H)}, \frac{2(N \cdot H)(N \cdot \omega_i)}{(\omega_o \cdot H)}\}, \tag{14}$$

$$P = \frac{e^{-\tan^2(\alpha)/m^2}}{m^2 \cos^4 \alpha}. \tag{15}$$

U is a geometry term that represents shadowing and masking effects among microfacets, P is the Beckmann microfacet distribution, F_r is the reflective Fresnel term, ω_i is the incident light direction, ω_o is the view direction, N is the surface normal, H is the halfway vector between the light and view directions, and α is the halfway angle between N and H. The free variables are the material roughness m and refractive index η.

Based on measured data [18], we set m_b, the roughness of skin, and η_b, the refractive index of skin, to $m_b = 0.3$ and $\eta_b = 1.38$, respectively. The refractive index of cosmetics, however, is difficult to measure [6]. The main ingredients of foundations are mainly water($\sim 30\%$) and oil($\sim 70\%$) [21]. Lipstick primarily consists of oil and wax. The refractive indices of water, oil, and wax are 1.33, 1.46, and 1.44 [4]. Based on these properties, we approximate the refractive index of foundation and lipstick as $\eta_f = 1.42$ and $\eta_l = 1.45$.

For the reflective Fresnel term, we utilize Schlick's approximation [15], expressed as

$$F_r(\omega_i \cdot H, \eta) = f_0 + (1 - f_0)(1 - \omega_i \cdot H)^5, \tag{16}$$

where

$$f_0 = (\frac{1 - \eta}{1 + \eta})^2. \tag{17}$$

So with the refractive indices for bare skin and cosmetics, the Fresnel term is calculated as

$$F_r(\eta_b) = 0.025 + 0.957(1 - \omega_i \cdot H)^5, \tag{18}$$

$$F_r(\eta_f) = 0.030 + 0.970(1 - \omega_i \cdot H)^5, \tag{19}$$

$$F_r(\eta_l) = 0.034 + 0.966(1 - \omega_i \cdot H)^5. \tag{20}$$

From these formulas, we approximate the ratio between the Fresnel terms of bare skin and cosmetics (only foundation and lipstick are considered to have specular highlight layers in our work) as

$$\frac{F_r(\eta_b)}{F_r(\eta_c)} \approx 1. \tag{21}$$

For the Beckmann microfacet distribution term in Eq. (15), we make use of an approximation that $\exp(-\tan^2 \alpha / m^2) / \cos^4 \alpha \approx 1$, which is explained in Appendix A. With this approximation, the distribution can be expressed more simply as

$$P \approx \frac{1}{m^2}. \tag{22}$$

Combining Eq. (13), Eq. (21), and Eq. (22), we can represent the ratio between the specular reflectance of skin $f_s(m_b, \eta_b)$ and cosmetics $f_s(m_c, \eta_c)$ as

$$\frac{f_s(m_b, \eta_b)}{f_s(m_c, \eta_c)} = \frac{m_c^2}{m_b^2} \cdot \frac{F_r(\eta_b)}{F_r(\eta_c)} \approx \frac{m_c^2}{m_b^2}, \tag{23}$$

where $m_b = 0.3$.

Based on the ratio in Eq. (23), the specular highlight S_c for cosmetic c is computed as

$$S_c = \frac{m_b^2}{m_c^2} S_B, \tag{24}$$

where m_c is the cosmetic roughness and S_B is the specular highlight layer decomposed in Eq. (2).

In addition to specular highlight from the cosmetics layer, there is also specular reflection contributed by the skin layer, which is reduced twice by the Kubelka-Munk transmittance of the makeup layer as illustrated in Fig. 2(b). Combining the two specular components, we obtain the final specular highlight layer S_M in Eq. (3) as

$$S_M = T_c^2 \cdot S_B + \frac{m_b^2}{m_c^2} S_B. \tag{25}$$

4. Cosmetics Measurement and Simulation

To digitally apply a certain cosmetic product c, its material parameters $\Theta = \{S_c, K_c, \alpha_c, \beta_c, m_c\}$ need to be known. We recover these values using two images captured of the same face, without makeup (I_B) and with the cosmetic (I_M)[4]. These two images are aligned by thin plate splines [1] using an extended Active Shape Model [11], similar to [5]. After image alignment, the parameters Θ and cosmetic thickness field t are estimated by minimizing the following objective function via L-BFGS:

$$\operatorname*{argmin}_{\Theta, t} \lambda_A E_A + \lambda_D E_D + \lambda_S E_S + E_t \tag{26}$$

where λ_A, λ_D, λ_S balance the constraints on albedo energy E_A, diffuse shading energy E_D, specular highlight energy E_S, and the thickness smoothness energy E_t.

E_A measures the difference between the albedo layer of simulated makeup in Eq. (7) and that of captured makeup:

$$E_A = \sum_{p \in I_M} \| R_c(p) + \frac{T_c(p)^2 A_B(p)}{1 - R_c(p) A_B(p)} - A_M(p) \|^2. \tag{27}$$

E_D represents the difference between the diffuse shadings of simulated makeup in Eq. (8) and captured makeup:

$$E_D = \sum_{p \in I_M} (D_M(p) * G(\sigma) - D_B(p))^2. \tag{28}$$

[4]Since blush and eye shadow are normally applied after foundation, the barefaced image I_B for these two types of cosmetics includes foundation. We note that blush and eye shadow only change albedo, so only $\Theta = \{S_c, K_c\}$ need to be recovered for them. For these cosmetics, A_B is taken as the A_M for the underlying foundation.

E_S denotes the difference between simulated makeup (Eq. (25)) and captured makeup in the specular highlight layer:

$$E_S = \sum_{p \in I_M} ((T_c(p)^2 + \frac{m_b^2}{m_c^2}) \cdot S_B(p) - S_M(p))^2. \tag{29}$$

Finally, E_t is a smoothness term for the thickness field t:

$$E_t = \sum_{p,q \in \aleph} (t(p) - t(q))^2, \tag{30}$$

where $\aleph$ is the set of 4-connected neighbors in I_M.

After recovering the cosmetic parameters Θ, we can easily transfer its visual effects to any barefaced image with a user-defined cosmetic thickness map. In our experiments, we use a constant thickness for foundation and lipstick as well as a learned thickness distribution for blush and eye shadow. This transfer is computed layer by layer according to Eq. (7), Eq. (12) and Eq. (25). The three layers are then composed by Eq. (3).

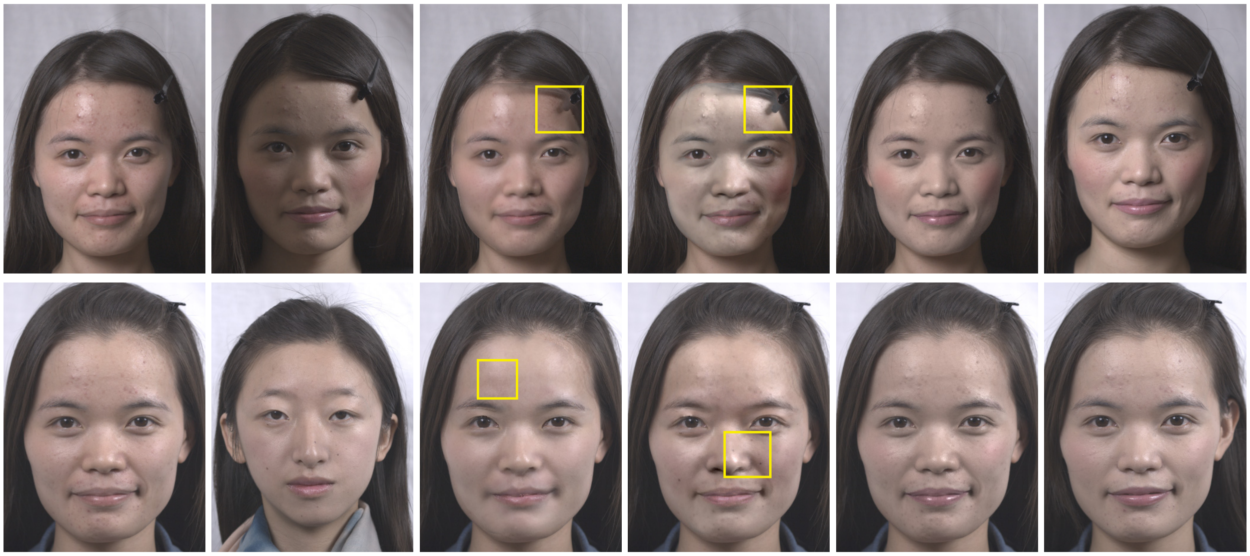
5. Results

To evaluate the proposed makeup model, we compare it to previous image-based makeup transfer techniques [5, 16]. Additional results are also reported for further examination of our method. For cosmetics measurement, we set the parameters $\{\lambda_A, \lambda_D, \lambda_S\}$ to $\{100, 10, 10\}$ for foundation, $\{100, 1, 50\}$ for lipstick, and $\{100, 0, 0\}$ for blush and eye shadow.

5.1. Comparisons

The comparisons to previous image-based makeup transfer methods [16, 5] are shown in Figure 3. Advantages of our approach are illustrated in these examples.

Since our method manipulates layer appearance in the target image according to makeup properties, rather than transfer makeup appearance from other images, it does not mistakenly transfer lighting effects from reference images. This is illustrated in the first row of Fig. 3, which shows an example of the same face used as the reference image but with lighting conditions different from the target image. In the makeup transfer models, image gradients from the reference image are blended with those of the target image [16] or used to replace the gradients in the target image [5]. Since the gradient information is influenced by illumination, the lighting effects from the reference image are also transferred to the target image. This is exhibited in the yellow boxes of (c) and (d), where highlight and/or hairpin shadow are transferred as well as makeup appearance. Since the method in [16] uses a ratio between "after" and "before" makeup images in addition to the gradient transfer, it is somewhat less sensitive than [5] to illumination inconsistency if the "before" and "after" images are precisely aligned.

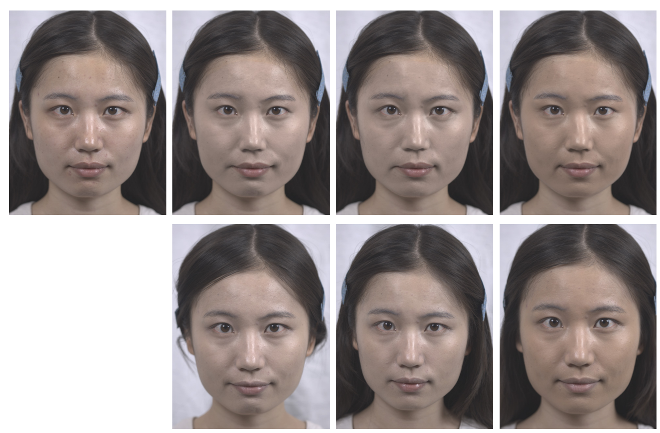


(a) (b) (c) (d) (e) (f)

Figure 3. Comparisons with previous image-based makeup transfer methods [16, 5]. (a) Target images. (b) Reference images with makeup, which are used by [16, 5] but not by our method. The reference images without makeup that are used in [16] are not shown. (c) Results of [16]. (d) Results of [5]. (e) Our results. (f) Target faces actually wearing the cosmetics, which serves as unaligned ground truth. In the first row, the target and reference images were captured of the same face under different lighting conditions. In the second row, the target and reference images are of different faces under the same lighting condition. The yellow boxes highlight errors in makeup transfer.

Our method similarly avoids transfer of personal details when the reference and target are different people, as shown in the second row of Fig. 3, which presents an example where the lighting condition of the reference and target are the same but the faces are different. The personal detail transfer in [5], as exhibited by the dark spots in the yellow box in (d), results from its use of alpha blending for color transfer and linear combinations of the reference and target for skin detail transfer. The method assumes that makeup conceals personal details, but this is often not the case, as illustrated here with a light application of foundation in (b). Dark spots such as these are removed prior to makeup transfer in [16] via independent components analysis. However, its use of gradient transfer leads to skin smoothing as shown in the yellow box in (c), where the smooth skin of the reference is transferred to the target. This transfer of smooth skin produces a result inconsistent with the approximate ground truth shown in (f), where the blemishes are reduced in appearance but not completely obscured.

Differences in diffuse shading are also visible between our results and those of image-based makeup transfer. As mentioned previously, the soft, translucent appearance of skin is a result of subsurface scattering, which is reduced when makeup is applied. The resulting "hardening" of appearance amplifies fine-scale surface details as seen in the forehead and cheek areas of the real makeup references in (f). (Please zoom into the electronic file to more clearly see this.) The makeup transfer results in (c) and (d) do not exhibit this hardness, but rather the skin looks about as soft and translucent as in the target images in (a). By contrast, our results in (e) exhibit the fine-scale surface texture caused by the makeup. This is produced by deconvolution of the diffuse shading layers from the target images.



(a) (b) (c) (d)

Figure 4. Different foundations. (a) Without makeup. (b) Ivory foundation. (c) Natural foundation. (d) Dark brown foundation. The first row presents our simulated results and the second row shows images of real makeup as references.

5.2. Additional results

We present some additional results of our method on different cosmetics, namely foundations in Fig. 4, lipsticks in Fig. 5 and eye shadows in Fig. 6, to demonstrate its ability

(a) (b) (c) (d)

Figure 5. Different lipsticks. (a) Without makeup. (b) Lipstick 1. (c) Lipstick 2. (d) Lipstick 3. The first row contains our simulated results, and the second row shows images of real makeup as references. Note that the lip configurations in the references do not necessarily match the target image.

to capture the visual effects of different products.

In Fig. 4, results for different foundations are shown. The foundations differ in color (ivory, natural, and dark brown), and also differ slightly in reflectance, as lighter-color foundations generally contain more water than darker foundations. Our method is shown to closely approximate the colors. Slight differences in specular highlights are also exhibited, appearing a bit weaker for darker foundations.

In Fig. 5, we display our results for different lipsticks. Besides the obvious color differences, lipsticks also affect specular highlights differently according to their own optical properties. From the reference images with real makeup, it can be seen that the lipsticks increase in glossiness from left to right. These differences are reflected in the simulated results. The results also illustrate a shortcoming of our approach. If a glossy lipstick generates specular highlights in areas that do not contain highlights in the target image, our method would not be able to reproduce them, since it operates by altering the specular highlights layer of the target image. To synthesize the additional highlight areas due to glossy lipstick, the lip geometry and lighting conditions would need to be recovered.

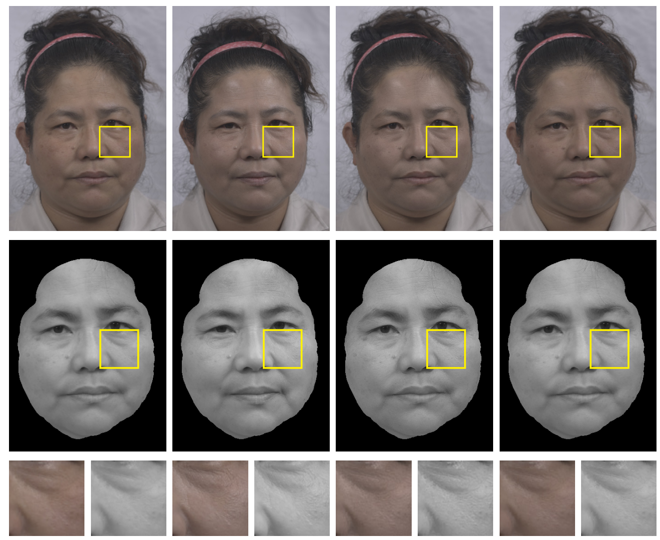
Besides the obvious color differences, lipsticks also affect specular highlights differently according to their own optical properties. From the reference images with real makeup, it can be seen that the lipsticks increase in glossiness from left to right. These differences are reflected in the simulated results. The results also illustrate a shortcoming of our approach. If a glossy lipstick generates specular highlights in areas that do not contain highlights in the target image, our method would not be able to reproduce them, since it operates by altering the specular highlights layer of the target image. To synthesize the additional highlight areas due to glossy lipstick, the lip geometry and lighting conditions would need to be recovered.

As mentioned in Tab. 1, eye shadow is assumed to affect only the albedo layer. Simulations of different eye shadows are shown in Fig. 6.

The results of our method for foundation applied with different thickness are displayed in Fig. 7. It can be seen that the skin without makeup in (a) is relatively soft and translucent. By contrast, the skin with heavy foundation in (b) appears more opaque with greater surface detail. Our simulation with heavy foundation in (c) exhibits similar characteristics, and with light foundation in (d) the surface detail is less pronounced.

(a) (b) (c) (d)

Figure 6. Different eye shadows. (a) Without makeup. (b) Eye shadow 1. (c) Eye shadow 2. (d) Eye shadow 3. The first row contains our simulated results, and the second row shows images of real makeup as references.



(a) (b) (c) (d)

Figure 7. Different foundation thickness. (a) Without makeup. (b) Real image with heavy foundation. (c) Synthesized image with heavy foundation. (d) Synthesized image with light foundation. The first row shows color images and the second row shows the corresponding diffuse shading layers. The third row displays close-up views of approximately the same areas of the color images and diffuse shading layers. Please zoom into the electronic file for closer inspection.

Finally, we present a couple more examples of our results in Fig. 8 for two different makeup styles on different subjects. Photos of the subjects actually wearing the simulated cosmetics are provided for comparison. In these comparisons, our results appear to closely approximate the references.

6. Conclusion

We presented a technique for simulating makeup in a photo by manipulating its intrinsic image layers according to proposed adaptations of physically-based reflectance models. Various cosmetic products can be synthesized in

(a) (b) (c) (d) (e)

Figure 8. Different makeup styles. (a) Without makeup. (b) Our result for makeup style 1 (foundation+lipstick+blush). (c) Real makeup reference for makeup style 1. (d) Our result for makeup style 2 (foundation+lipstick+blush+eye shadow). (e) Real makeup reference for makeup style 2.

this manner from measurements of their optical properties. While a few approximations are made in formulating the layer transformations, the simulated results closely resemble the actual appearance of the corresponding cosmetics.

We note that since our method relies on accurate decomposition of intrinsic image layers, errors in this decomposition will degrade the quality of our simulation results. The topic of intrinsic image estimation has received increased attention in the past few years, and advances in this area would benefit our makeup synthesis technique.

In future work, we plan to improve the processing speed of our method. Currently, about 99% of the computation time is spent on deconvolution for the diffuse shading layer. There is the potential to accelerate this computation significantly by implementing the sparse linear system solver on the GPU. With increases in speed, an extension of this work to live video may become feasible.

Acknowledgements

The authors thank makeup artists Yang Li, Shuying Wu, Yan Peng and the models. This work was partially supported by NSFC (No. 61272305) and the National Program for Special Support of Eminent Professionals.

A. Approximation for the Beckmann microfacet distribution

The approximation $\exp(-\tan^2\alpha/m^2)/\cos^4\alpha \approx 1$ in Sec. 3.2.3 is used to simplify the form of the Beckmann microfacet distribution. This approximation is made based on the observations that most highlight energy is contributed from small values of the halfway angle α, and the approximated quantity does not change drastically for small values of α as illustrated in Fig. 9. For the roughness values that we measured for a few different foundations, the value of the approximated quantity is close to 1 for $\alpha < 10°$. For skin and cosmetics like lipstick that have lower roughness values, the approximated quantity changes more rapidly, but the highlight energy for those glossier materials is concentrated more tightly around $0°$. As a result, the approximation in Eq. (22) is adequate for our purposes, as demonstrated in the results of Sec. 5.

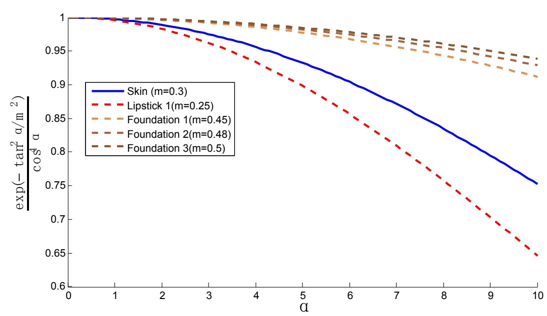


Figure 9. Approximation for the Beckmann microfacet distribution. The curves represent different roughness values and are shown for the range of $\alpha \in [0°, 10°]$.

References

[1] F. L. Bookstein. Principal warps: Thin-plate splines and the decomposition of deformations. *IEEE Trans. Pattern Anal. Mach. Intell.*, 11(6):567–585, June 1989.

[2] T. A. Davis. Algorithm 915, suitesparseqr: Multifrontal multithreaded rank-revealing sparse qr factorization. *ACM Trans. Math. Softw.*, 38(1):8:1–8:22, 2011.

[3] M. Doi, R. Ohtsuki, and S. Tominaga. Spectral estimation of skin color with foundation makeup. In H. Klviinen, J. Parkkinen, and A. Kaarna, editors, *SCIA*, volume 3540 of *Lecture Notes in Computer Science*, pages 95–104. Springer, 2005.

[4] J. Goldsmith and R. Kanthack. *Tables of Refractive Indices: Oils, fats and waxes, comp. by R. Kanthack*. Tables of Refractive Indices. A. Hilger, limited, 1921.

[5] D. Guo and T. Sim. Digital face makeup by example. In *Proc. of IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2009.

[6] C.-G. Huang, W.-C. Lin, T.-S. Huang, and J.-H. Chuang. Physically-based cosmetic rendering. In *Proceedings of the ACM SIGGRAPH Symposium on Interactive 3D Graphics and Games*, I3D '13, pages 190–190, New York, NY, USA, 2013. ACM.

[7] J. Jimenez, V. Sundstedt, and D. Gutierrez. Screen-space perceptual rendering of human skin. *ACM Trans. Appl. Percept.*, 6(4):23:1–23:15, Oct. 2009.

[8] P. Kubelka and F. Munk. Ein beitrag zur optik der farbanstriche. *Z. Tech. Phys*, 12:593–601, 1931.

[9] C. Li, K. Zhou, and S. Lin. Intrinsic face image decomposition with human face priors. In *Proc. of European Conf. on Computer Vision (ECCV)*, 2014.

[10] L. Liu, H. Xu, J. Xing, S. Liu, X. Zhou, and S. Yan. "wow! you are so beautiful today!". In *Proceedings of the 21st ACM International Conference on Multimedia*, MM '13, pages 3–12, New York, NY, USA, 2013. ACM.

[11] S. Milborrow and F. Nicolls. Locating facial features with an extended active shape model. In *Proceedings of the 10th European Conference on Computer Vision: Part IV*, ECCV '08, pages 504–513, Berlin, Heidelberg, 2008. Springer-Verlag.

[12] Y. Moriuchi, S. Tominaga, and T. Horiuchi. Precise analysis of spectral reflectance properties of cosmetic foundation. In A.-B. Salberg, J. Y. Hardeberg, and R. Jenssen, editors, *SCIA*, volume 5575 of *Lecture Notes in Computer Science*, pages 138–148. Springer, 2009.

[13] C. Saint Louis. Up the career ladder, lipstick in hand. `http://www.nytimes.com/2011/10/13/fashion/makeup-makes-women-appear-more-competent-study.html`, Oct. 2011.

[14] K. Scherbaum, T. Ritschel, M. Hullin, T. Thormählen, V. Blanz, and H.-P. Seidel. Computer-suggested facial makeup. *Comp. Graph. Forum (Proc. Eurographics 2011)*, 30(2), 2011.

[15] C. Schlick. An inexpensive BRDF model for physically-based rendering. *Computer Graphics Forum*, 13(3), 1994.

[16] W.-S. Tong, C.-K. Tang, M. S. Brown, and Y.-Q. Xu. Example-based cosmetic transfer. *Computer Graphics and Applications, Pacific Conference on*, 0:211–218, 2007.

[17] K. Torrance and E. Sparrow. Theory for off-specular reflection from roughened surfaces. *J. Optical Soc. America*, 57:1105–1114, 1967.

[18] T. Weyrich, W. Matusik, H. Pfister, B. Bickel, C. Donner, C. Tu, J. McAndless, J. Lee, A. Ngan, H. W. Jensen, and M. Gross. Analysis of human faces using a measurement-based skin reflectance model. *ACM Trans. Graph.*, 25(3):1013–1024, July 2006.

[19] F. Yang, J. Wang, E. Shechtman, L. Bourdev, and D. Metaxas. Expression flow for 3d-aware face component transfer. *ACM Trans. Graph.*, 30(4):60:1–60:10, July 2011.

[20] Q. Zhao, P. Tan, Q. Dai, L. Shen, E. Wu, and S. Lin. A closed-form solution to retinex with nonlocal texture constraints. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 34(7):1437–1444, July 2012.

[21] J. Ziming Sun, M. C. Erickson, and J. W. Parr. Refractive index matching and clear emulsions. *International Journal of Cosmetic Science*, 27(6):355–356, 2005.